Unwarranted Gender Disparity and Its Drivers in Online P2P Lending

Xudong Shen, NUS
Tianhui Tan, NUS
Tuan Q. Phan, HKU
Jussi Keppo, NUS

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Background

- Discrimination can arise in various ways…
  - **Taste**
  - **Beliefs** → systematically unequal prediction about expected outcome
- Uncovering what drives discrimination is important…
  - for judging the legality of observed disparity
  - for designing policy interventions
    - policy that corrects inaccurate beliefs do not mitigate taste
- Existing works suffer an **underidentification** problem of the discrimination drivers:
  - Taste and beliefs can be observationally equivalent [Bohren et al., 2019]
  - To technically avoid underidentification, the literature relies on restricted decision models that assume (i) drivers cannot all co-exist, or (ii) the decision maker's beliefs are accurate
  - These assumptions are unrealistic, and threat the validity of findings

Summary of This Work

- How much can we infer about **discrimination drivers** from observational data?
  - Three distinct drivers: **personal taste**, **unequal first-order belief**, and **unequal second-order belief**
- Existing works suffer an **underidentification** problem:
  - Two DoF underidentification for the three discrimination drivers
- This paper exemplifies an **improved identification in P2P Lending**
  1. Develop a decision model that characterises (i) the structure of the investors' narrow legitimate objective—the loans' return rate—and (ii) the platform's All-or-Nothing (AON) crowdfunding policy, but without assuming accurate beliefs or some driver non-exists
  2. **Improved identification in the limiting form of this model with increasing # investors**
  3. Investigate data from one of the largest P2P lending platforms in China
  4. Find evidence of female favouritism, and partially identify discrimination drivers
  5. The investors indeed have **overrated beliefs about their signal reliabilities**, rejecting the accurate beliefs assumption

Def. Decision Model

- A decision model that applies to many contexts: single decision maker decides $D_i \in \{0,1\}$ for subjects $i \in [I]$ with gender $G_i \in \{m, f\}$, based on predicted expected worthiness $\tilde{\lambda}_i$
- **Data Generating Process (DGP):**

$$\lambda_i \mid (G_i = g) \sim N(\mu_g, (\sigma_{g,0})^2)$$

Actual worthiness λ_i sampled from Gaussian

$$\hat{\lambda}_i \mid (G_i = g) = \lambda_i + \sigma_{g,1}\epsilon_i, \epsilon_i \sim N(0,1)$$

Observe noisy worthiness $\hat{\lambda}_i$

DGP parameters $\{\mu_g, \sigma_{g,0}, \sigma_{g,1}\}_{g \in \{m,f\}}$

- **Decision Making:**

Decision maker holds beliefs about DGP parameters $\{\hat{\mu}_g, \hat{\sigma}_{g,0}, \hat{\sigma}_{g,1}\}_{g \in \{m,f\}}$

$$\tilde{\lambda}_i \mid (G_i = g) = \mathbb{E}[\lambda_i \mid \hat{\lambda}_i, \hat{\mu}_g, \hat{\sigma}_{g,0}, \hat{\sigma}_{g,1}]$$

Compute expected worthiness $\tilde{\lambda}_i$ using beliefs

$$D_i \mid (G_i = g) = 1[\tilde{\lambda}_i \geq \pi_g]$$

Decide D_i by thresholding

Decision parameters $\{\pi_g, \hat{\mu}_g, \hat{\sigma}_{g,0}, \hat{\sigma}_{g,1}\}_{g \in \{m,f\}}$

Def. Gender Discrimination Drivers

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- **Gender taste: decision threshold $\pi_f \neq \pi_m$**
  - Apply double standards
  - Perceive direct utility in lending to female/male

Def. Gender Discrimination Drivers

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- **Unequal first-order belief: Worthiness Mean Belief $\hat{\mu}_f \neq \hat{\mu}_m$**
  - Believe female/male has higher mean worthiness
  - Systematic prediction mistake about expected worthiness

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- **Unequal second-order belief: Signal Reliability Belief $\hat{\gamma}_f \neq \hat{\gamma}_m$**
  - **Signal Reliability Belief** $\hat{\gamma}_g = (\hat{\sigma}_{g,1})^{-2} \,/\, \left((\hat{\sigma}_{g,0})^{-2} + (\hat{\sigma}_{g,1})^{-2}\right)$
  - $\hat{\gamma}_g$ captures the combined effect of $\hat{\sigma}_{g,0}, \hat{\sigma}_{g,1}$ on decisions
  - Higher $\hat{\gamma}_g$ means the decision maker believes its observation $\hat{\lambda}_i$ is more reliable
  - Systematic prediction mistake about expected worthiness

Underidentification Problem

- **Gender taste: decision threshold $\pi_f \neq \pi_m$**
- **Unequal first-order belief: Worthiness Mean Belief $\hat{\mu}_f \neq \hat{\mu}_m$**
- **Unequal second-order belief: Signal Reliability Belief $\hat{\gamma}_f \neq \hat{\gamma}_m$**

- In this decision model
    - **we can only identify one value for the three decision parameters π_g, $\hat{\mu}_g$, $\hat{\gamma}_g$**
    - **Two DoF underidentification**

- In the literature:
    - aka. observational equivalence between taste and beliefs
    - [Bohren et al., 2019] studies exactly this model and proposes to identify two DoF isodiscrimination plane

Def. P2P Decision Model

- Feature 1: **structure of investor's narrow legal objective**
  - Investors decide D_i based on expected return rate
  - Return rate can be expressed a product between repayment ratio and (1+interest rate)
  - interest rate is fully observed

$$D_i \mid (G_i = g) = 1[\tilde{\lambda}_i \geq \pi_g]$$

$$D_i \mid (G_i = g) = 1[\tilde{Y}_i \geq \pi_g] = 1[\tilde{\lambda}_i(1 + R_i) \geq \pi_g]$$

Expected worthiness $\tilde{\lambda}_i$

Decision threshold π_g

Expected return rate $\tilde{Y}_i$

Expected repayment ratio $\tilde{\lambda}_i$, reflects trustworthiness

Listing's interest rate R_i, fully observed

Decision threshold π_g

Def. P2P Decision Model

- Feature 2: **All-or-Nothing crowdfunding policy**
  - Loan amount B_i
  - Investors $j \in [J]$ make individual subscription decisions $D_i^{(j)}$, and subscribe amount $I_i^{(j)}$ if $D_i^{(j)} = 1$

$$D_i \mid (G_i = g) = 1[\tilde{\lambda}_i(1 + R_i) \geq \pi_g]$$

expected repayment ratio $\tilde{\lambda}_i$

Listing's interest rate R_i, fully observed

Expected return rate $\tilde{\lambda}_i(1 + R_i)$

Decision threshold π_g

$$D_i^{(j)} \mid (G_i = g) = 1[\tilde{\lambda}_i^{(j)}(1 + R_i) \geq \pi_g^{(j)}]$$

$$D_i = 1[\sum_{j=1}^{J} D_i^{(j)} I_i^{(j)} \geq B_i]$$

Individual subscription decision $D_i^{(j)}$

Individual subscription amount $I_i^{(j)}$

Loan Amount B_i

Loan outcome D_i

Improved Identification in P2P Lending

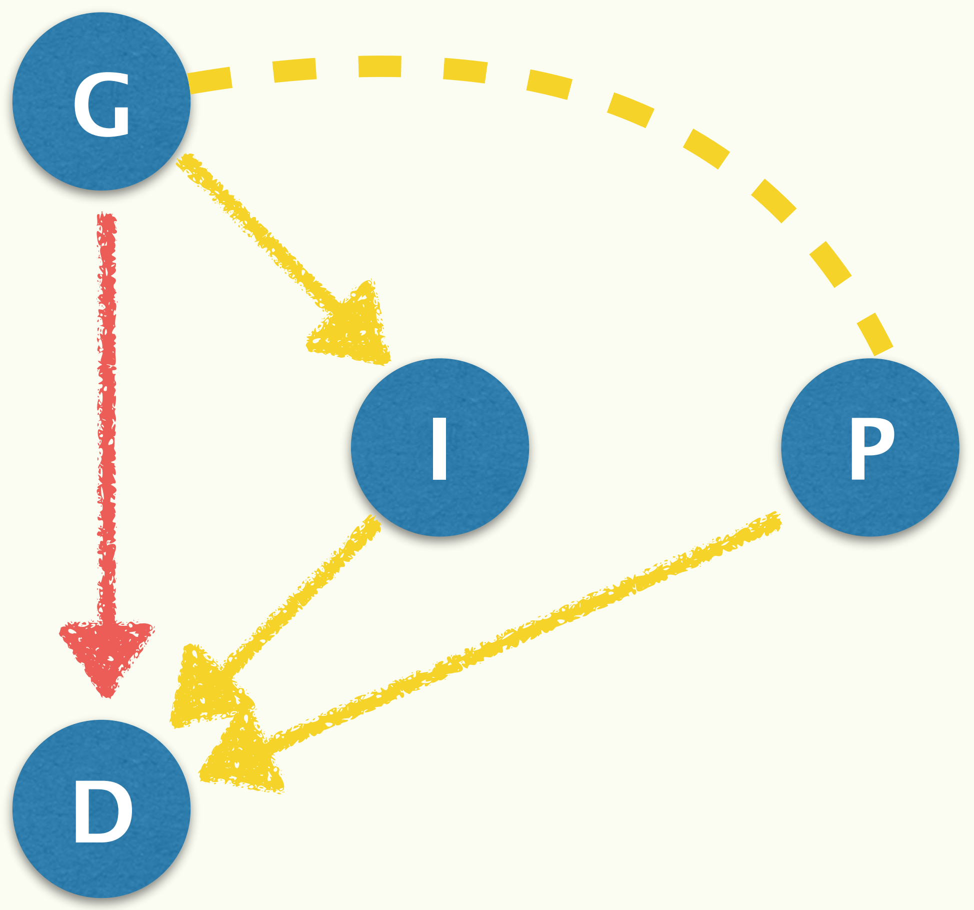
- The P2P decision model converges to a limiting type when # investors $\rightarrow \infty$
  - because of the AON policy, **loan outcomes D_i are effectively determined by the most lenient investor** when # investors increases
  - Give rise to **a switchpoint model** where loans whose interest rate are higher face different decision parameters than the loans whose interest rate are lower

$$D_i \mid (G_i = g) \sim \begin{cases} Bern\left(p = \Phi\left(\frac{1}{\sigma_{g,1}}\lambda_i - \frac{1}{\sigma_{g,1}} \times \underbrace{(\pi_g/\hat{\gamma}_g)}_{\underline{c_{g,1}}} \times \frac{1}{1+R_i} + \frac{1}{\sigma_{g,1}} \times \underbrace{((1/\hat{\gamma}_g - 1)\hat{\mu}_g)}_{\underline{c_{g,2}}}\right)\right), & \text{if } R_i < \underline{\pi_g}/\overline{\hat{\mu}_g} - 1, \\ Bern\left(p = \Phi\left(\frac{1}{\sigma_{g,1}}\lambda_i - \frac{1}{\sigma_{g,1}} \times \underbrace{(\pi_g/\hat{\gamma}_g)}_{\overline{c_{g,1}}} \times \frac{1}{1+R_i} + \frac{1}{\sigma_{g,1}} \times \underbrace{((1/\hat{\gamma}_g - 1)\hat{\mu}_g)}_{\overline{c_{g,2}}}\right)\right), & \text{if } R_i > \underline{\pi_g}/\overline{\hat{\mu}_g} - 1, \end{cases}$$

- **Exact identification or one DoF underidentification depends on whether the loans' interest rates cover both sides of the switchpoint**

Unwarranted Gender Disparity

- Unwarranted gender disparity compares loans of identical return rates.
  - $\Delta(y) = \mathbb{E}[D \mid G = m, Y = y] - \mathbb{E}[D \mid G = f, Y = y]$
- Observational comparison suffers included variable bias (IVB), which overlooks indirect disc. and proxy disc.



Two-stage predictor substitution (2SPS)

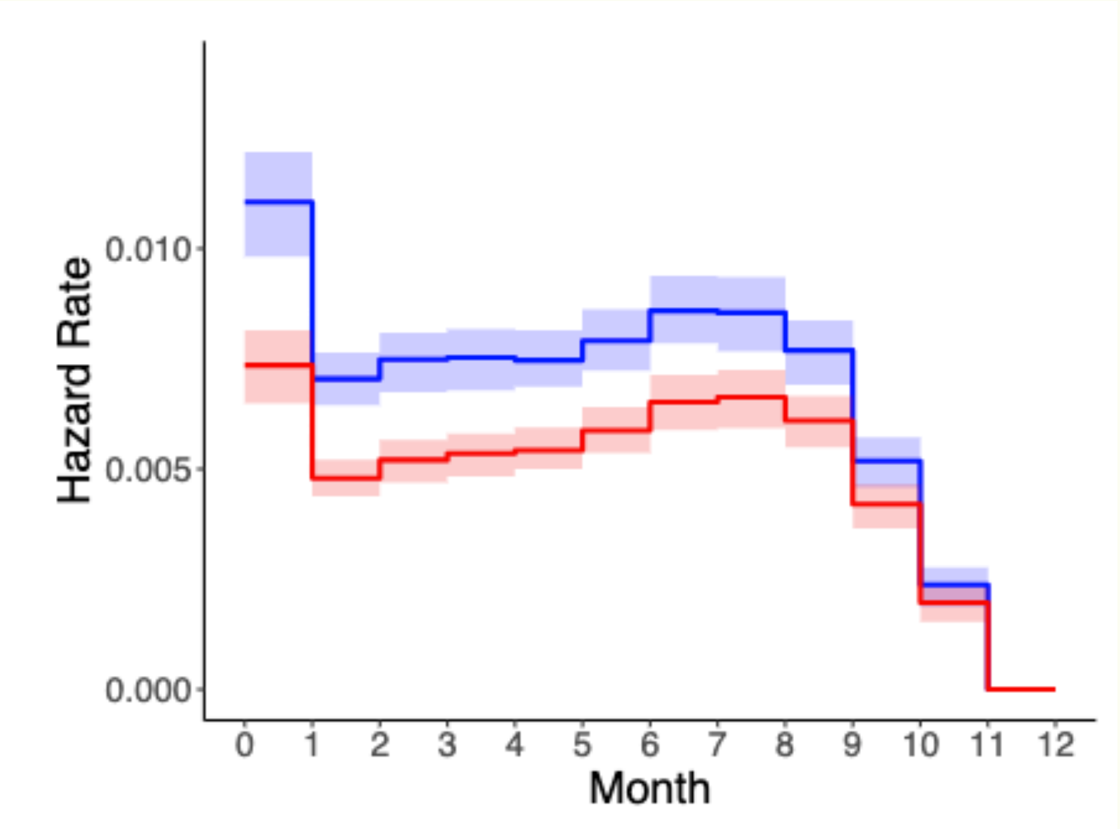
- **Missing data problem**: repayment ratio λ is observed conditional on successful loans…

$$\Delta(y) = \mathbb{E}[D \mid G = m, \boxed{\lambda} \times \boxed{(1 + R_i)} = y] - \mathbb{E}[D \mid G = f, \boxed{\lambda} \times \boxed{(1 + R_i)} = y]$$

$$D_i \mid (G_i = g) \sim \begin{cases} Bern\left(p = \Phi\left(\frac{1}{\sigma_{g,1}}\boxed{\lambda_i} - \frac{1}{\sigma_{g,1}} \times \underbrace{(\underline{\pi_g}/\overline{\hat{\gamma}_g})}_{\underline{c_{g,1}}} \times \boxed{\frac{1}{1+R_i}} + \frac{1}{\sigma_{g,1}} \times \underbrace{((1/\overline{\hat{\gamma}_g} - 1)\overline{\hat{\mu}_g})}_{\underline{c_{g,2}}}\right)\right), & \text{if } R_i < \underline{\pi_g}/\overline{\hat{\mu}_g} - 1, \\ Bern\left(p = \Phi\left(\frac{1}{\sigma_{g,1}}\boxed{\lambda_i} - \frac{1}{\sigma_{g,1}} \times \underbrace{(\overline{\pi_g}/\underline{\hat{\gamma}_g})}_{\overline{c_{g,1}}} \times \boxed{\frac{1}{1+R_i}} + \frac{1}{\sigma_{g,1}} \times \underbrace{((1/\underline{\hat{\gamma}_g} - 1)\underline{\hat{\mu}_g})}_{\overline{c_{g,2}}}\right)\right), & \text{if } R_i > \underline{\pi_g}/\overline{\hat{\mu}_g} - 1, \end{cases}$$

2SPS for discrimination driver estimation

Loan charc.



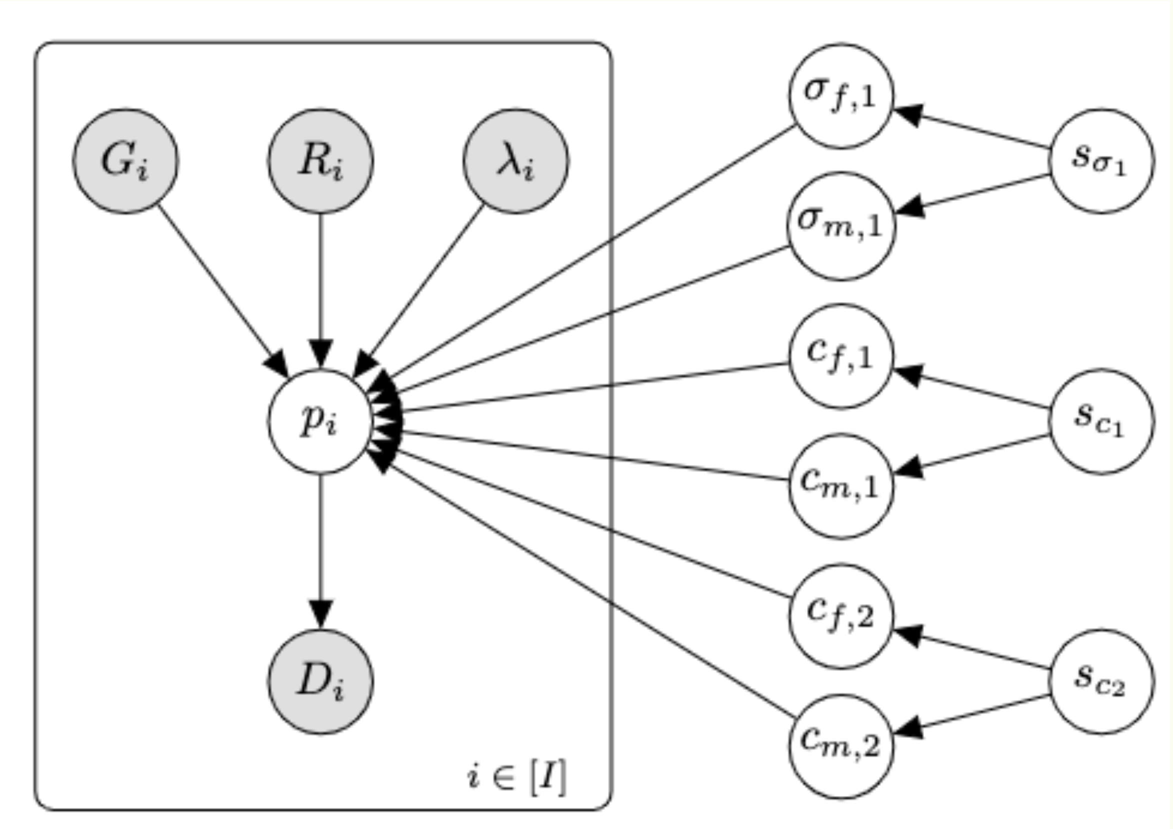
Survival model

Observed Interest Rate

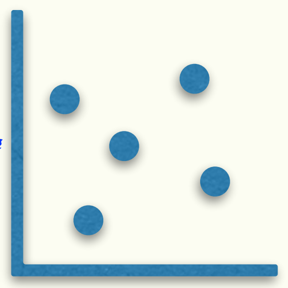
Predicted repayment ratio

Observed Return Rate

Predicted Return Rate



Bayesian Latent Variable Model



1st stage

2nd stage

Bootstrap both stages

Unwarranted Gender Disparity

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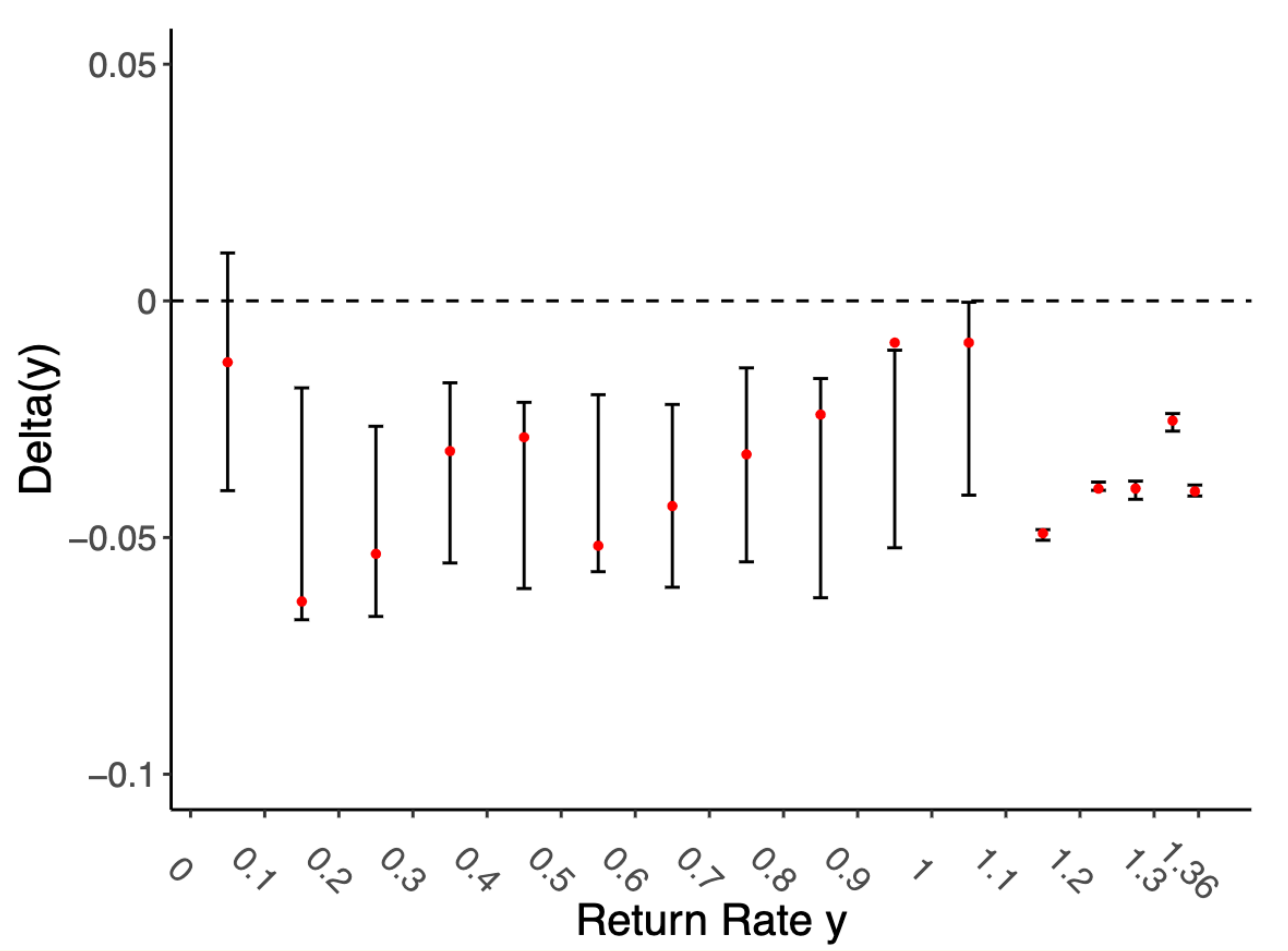

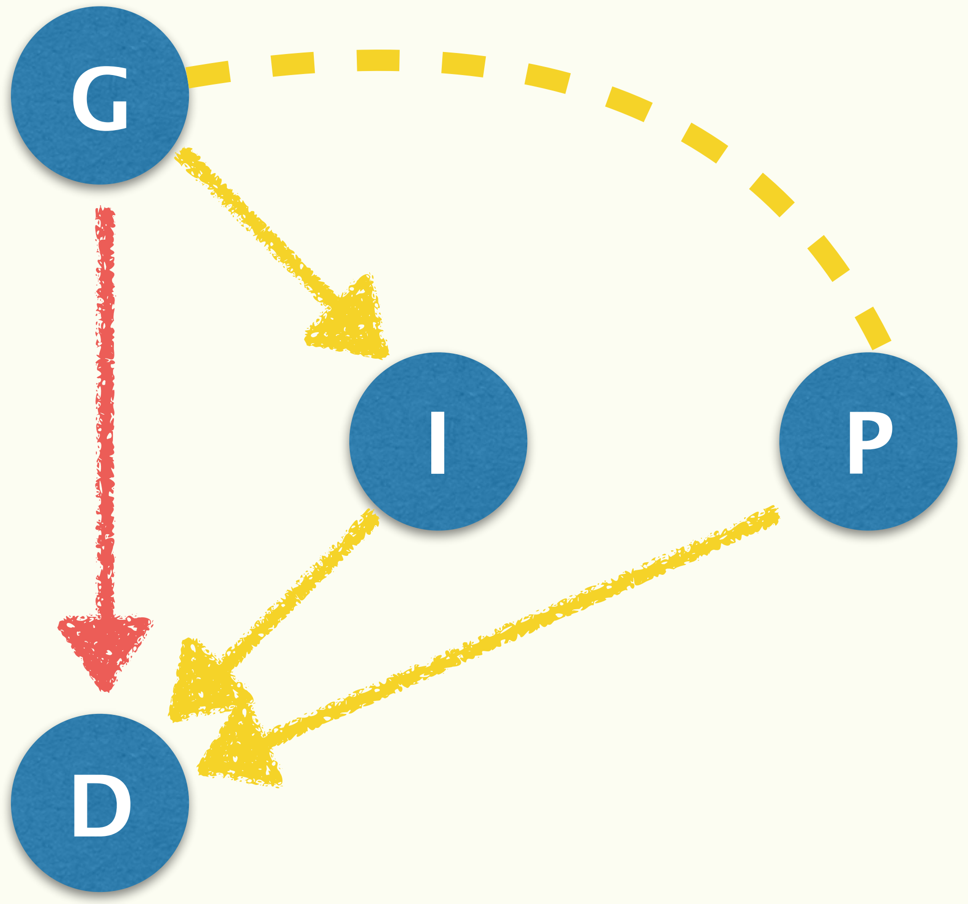

Table 3: Estimate of Gender Discrimination

Estimate	Lower 95% CI	Upper 95% CI
-0.0397	-0.0398	-0.0395

Unwarranted Gender Disparity

- 37.1% of unwarranted Gender Disparity can be explained by loan characteristics.
- Observational comparison has 44.6 % underestimation, due to IVB.

Table 3: Estimate of Gender Discrimination

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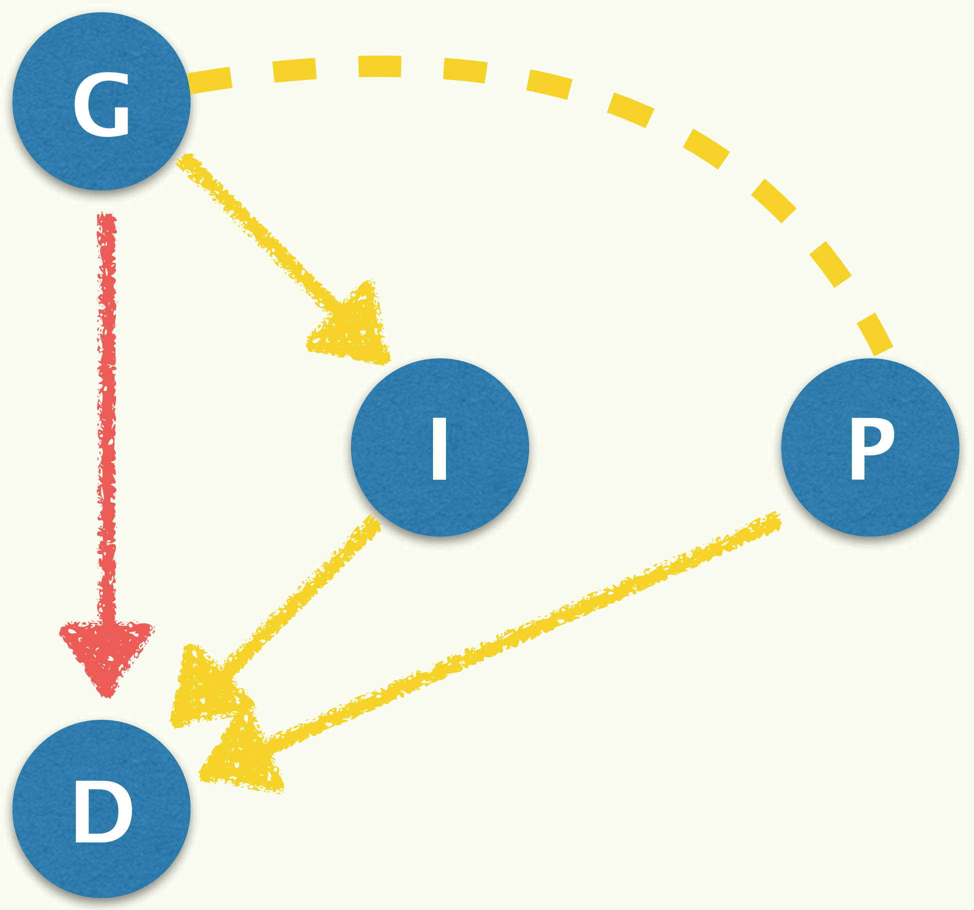
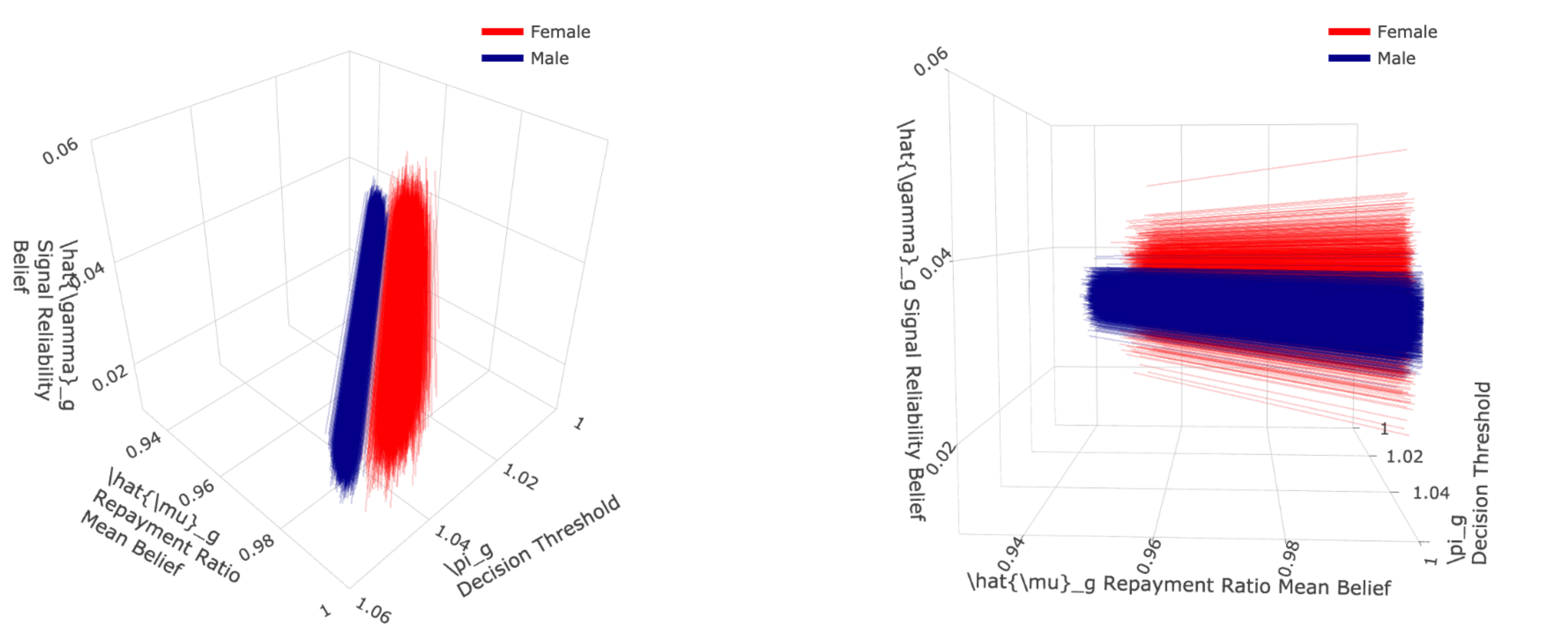
Table 4: OLS Estimates of Gender Discrimination

	Dependent variable: Loan Success		
	(1) Ours	(2)	(3)
Male	-0.0388	-0.0244	-0.0215
	(-0.0389,-0.0385)	(-0.0245,-0.0242)	(-0.0234,-0.0196)
Return Rate	✓	✓	
Loan Charc.		✓	✓



Drivers of Unwarranted Gender Disparity

Figure 7: Possible Decision Parameters Obtained From The Posterior

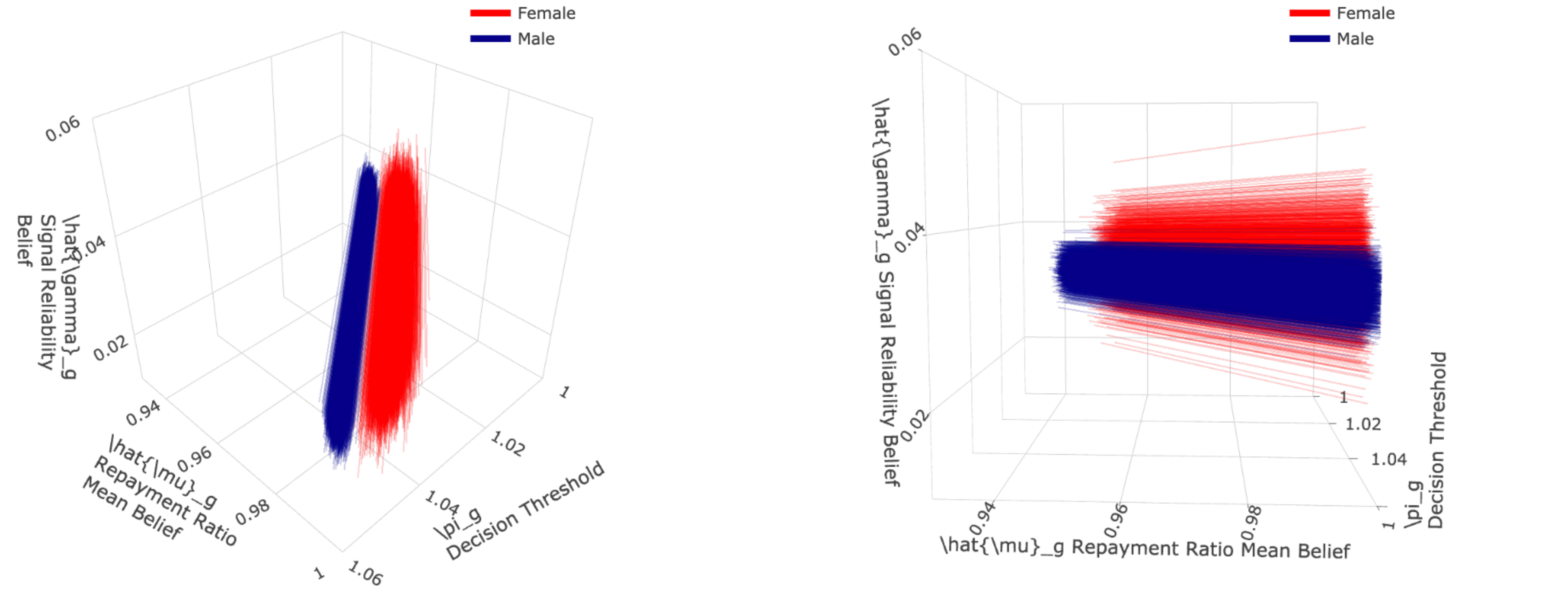


(a) (b)

Note: the left and right plots visualize, from two different viewpoints, the possible decision parameters traced out by 2000 random samples from male and female's posteriors.

Drivers of Unwarranted Gender Disparity

- **Unequal second-order belief driver is unpresent.**
  - Substantial overlap between signal reliability beliefs for male and female borrowers.
- **The second-order beliefs are inaccurate.**
  - The signal reliability beliefs are significantly higher than the investors' actual signal reliabilities, which are below 0.003.



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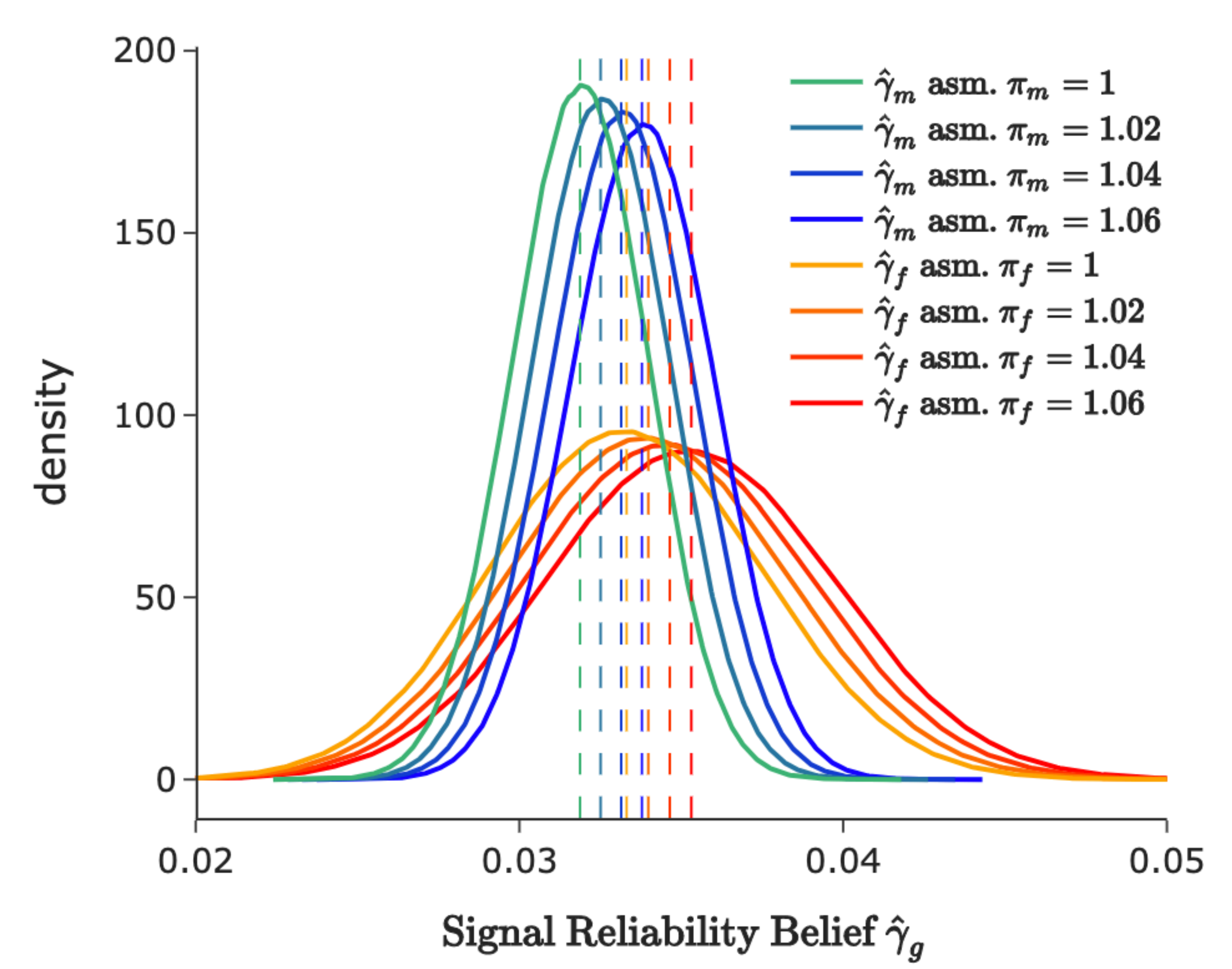
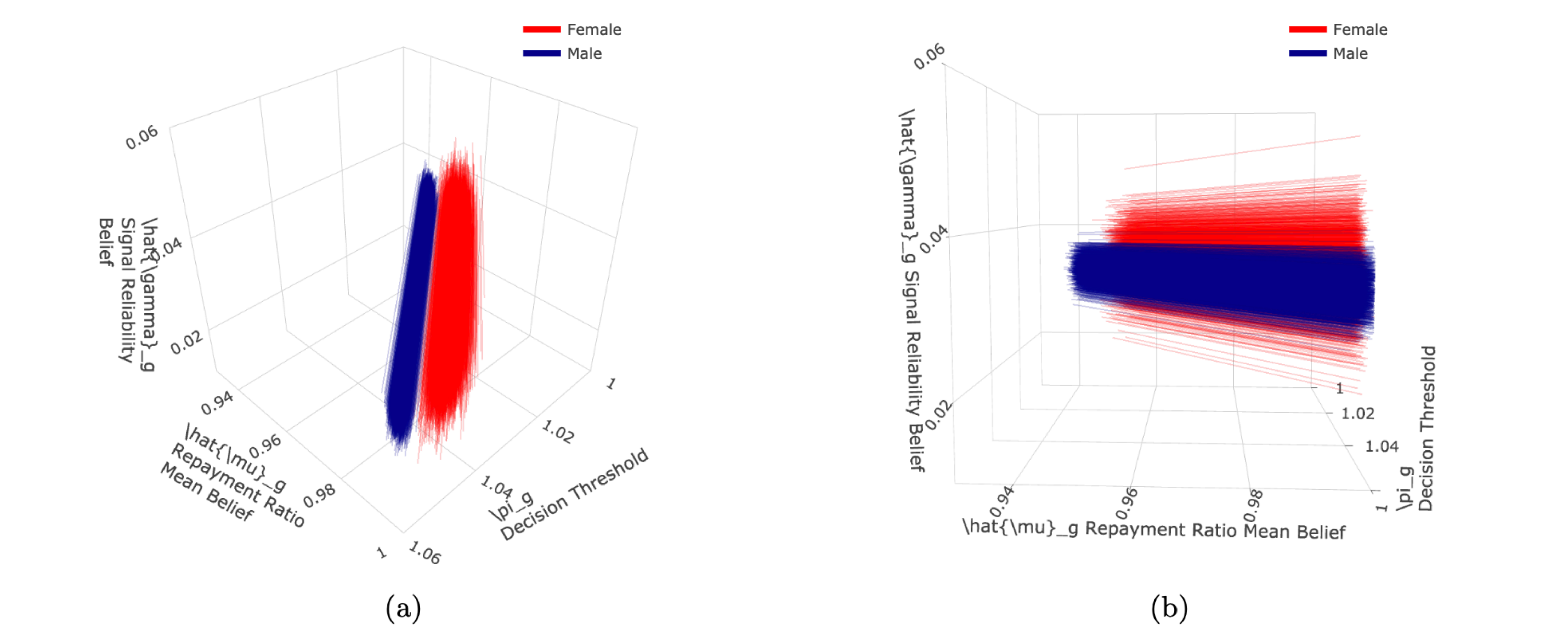


Drivers of Unwarranted Gender Disparity

- **Either gender taste favouring female or unequal first-order belief favouring female is present.**



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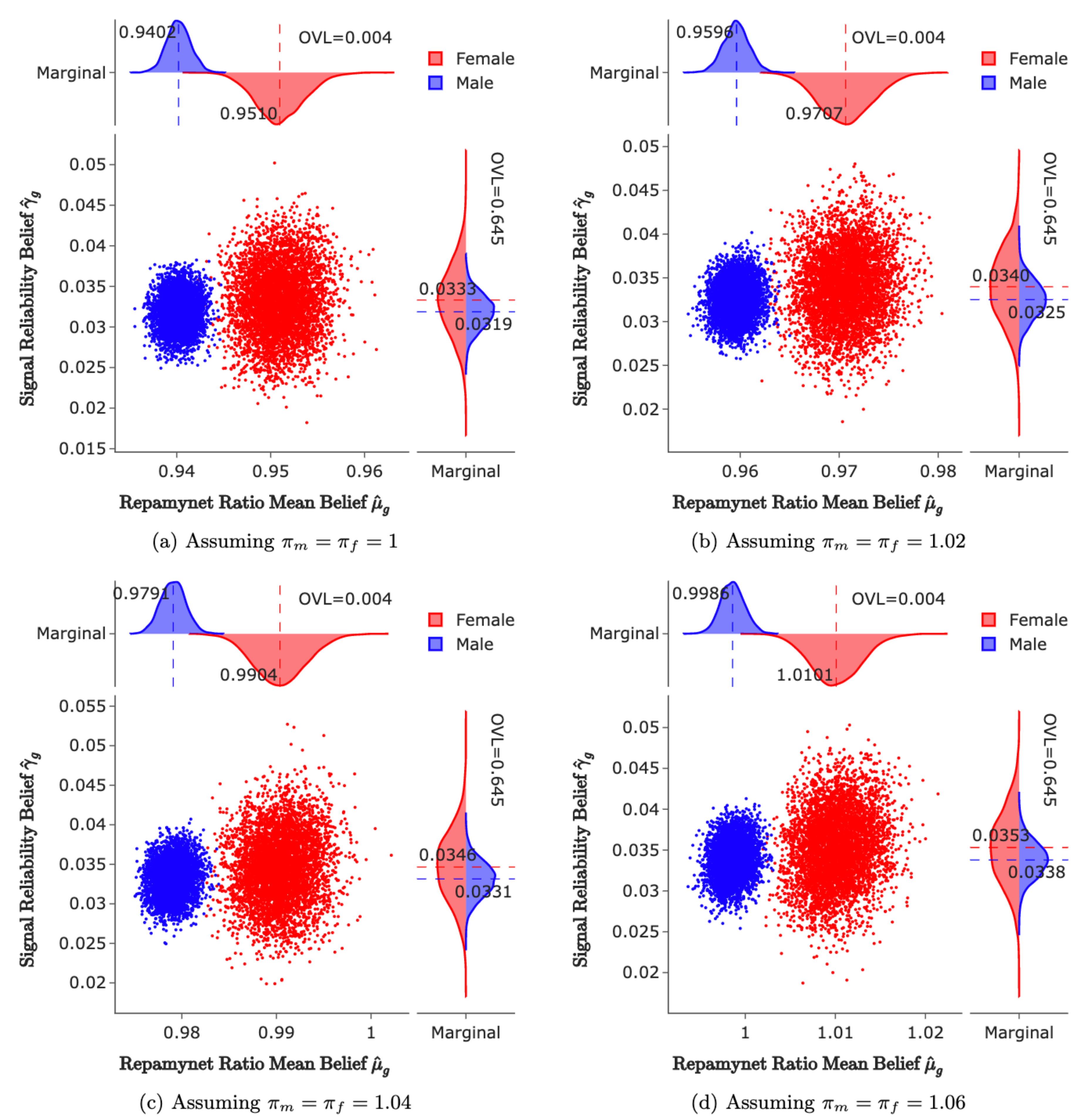

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